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DL-ML Based Prediction of Diabetic Retinopathy Using Fundus Images

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***Abstract*—Diabetic Retinopathy (DR) is a serious eye disease caused by diabetes and is one of the main reasons for vision loss across the world. If it is not detected early, it can lead to permanent blindness. Most current screening methods depend on manual examination by eye specialists, which is slow, costly, and difficult to access in rural areas. To overcome these limitations, this paper presents an automated system based on Deep Learning (DL) and Machine Learning (ML) for detecting and classifying DR from retinal fundus images. The system uses a Convolutional Neural Network (CNN) to identify different stages of DR such as mild, moderate, and severe with high accuracy. Along with diagnosis, the platform offers patient-friendly features including separate logins for doctors and patients, secure storage of medical history, and an AI chatbot for instant support and guidance. A simple and user-friendly interface makes the system easy to use. The results show reliable performance, proving that the system can provide fast, accurate, and accessible DR screening.**

***Index Terms*—Diabetic Retinopathy (DR), Deep Learning (DL), Convolutional Neural Networks (CNN), Machine Learning (ML), Rectified Linear Unit (ReLU).**

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the leading microvascular complications of diabetes and remains a major cause of preventable blindness worldwide. It occurs when persistently high glucose levels damage the retinal blood vessels, leading to leakage, formation of abnormal vessels, and progressive deterioration of vision [1]–[3]. Since DR develops gradually and often remains asymptomatic in the early stages, many patients fail to recognize its severity until substantial vision loss begins. With the rapid rise in global diabetes cases, the burden of DR is also increasing, creating an urgent need for efficient screening and monitoring systems [2], [7], [10]. Research suggests that a large proportion of diabetic individuals are likely to show signs of DR during their lifetime, reinforcing the importance of early detection and timely intervention [1], [2], [10].

Conventional screening for DR traditionally relies on ophthalmologists manually evaluating retinal fundus images to identify lesions such as microaneurysms, hemorrhages, and lipid exudates [2], [4], [7]. Although expert examination is effective, it is often time-consuming, labor-intensive, and requires skilled specialists who may not be readily available in many regions, especially rural or low-resource areas [2], [4]. Additionally, manual grading can lead to variations between specialists due to subjective interpretation, which may affect diagnostic consistency [3], [10]. These challenges highlight the need for automated, accurate, and scalable DR detection solutions that can support large populations and reduce the workload on healthcare providers [1], [2], [5].

Recent advances in Machine Learning and Deep Learning have significantly transformed medical image analysis. Convolutional Neural Networks have become a preferred model for DR detection due to their strong ability to automatically extract and learn important patterns from retinal images [1], [3], [5], [11]. Multiple studies have demonstrated that DL algorithms can identify DR lesions with high accuracy, surpassing many classical image-processing technique [1], [2], [5], [6], [10]. Hybrid architectures that combine different DL models further enhance performance by improving lesion detection and minimizing false-positive or false-negative predictions [1], [6], [8]. Techniques such as segmentation networks, attention-based models, and multi-label classification have also been successfully applied to improve lesion localization and stage classification [1], [6], [10]. Despite significant progress in DR detection research, many existing systems have limitations when applied in real-world healthcare environments. Several models focus exclusively on classification accuracy but do not provide essential practical features such as patient profiles, multi-user access, result history tracking, or communication support between doctors and patients [3], [7], [16].

To address these limitations, this work proposes a DL/ML-based DR detection system that not only focuses on high diagnostic accuracy but also incorporates patient-centric functionalities. The system uses CNN-based deep learning models to classify fundus images into DR severity stages and highlight relevant lesions with improved reliability [1], [2], [5], [11]. A dual-portal interface is provided, offering separate access for doctors and patients to ensure efficient workflow management and personalized dashboards [7], [12]. Doctors can upload and review retinal images, analyze model predictions, and monitor patient progress across multiple visits. Patients can view diagnostic reports, track changes in their retinal health, and receive timely updates or reminders [**?**], [**?**], [7].An intelligent AI-based chatbot is integrated into the system to help patients understand DR levels, treatment guidelines, general eye-care tips, and frequently asked questions.

This application paper describes the Proposed Methodol ogy in section II. Section III provides System Architecture and Mathematical Apporoach. Section IV covers Result and Performance Analysis. Section V provides Conclusion And Future Work.

II. PROPOSED METHODOLOGY

The proposed methodology introduce an automated diabetic retinopathy detection and it classifies stages of disease by using deep learning techniques.This system aims to help clinicians for early dignosis which help to minimize human errors and provide reliable real-time predictions,the workflow is illustarted in fig.1.

Fig. 1: Workflow of the Diabetic Retinopathy Detection and Classification System

A. Data Acquisition

The proposed system uses a ready-made dataset of fundus images collected from kaggle source publicly available dataset named diabetic retinopathy dataset which contains hospital-acquired images to ensure medical diversity the dataset contains total 2750 fundus images and images are labelled for severaity of disease which are classified into 5 stages as healthy,mild, moderated, proliferative and severe the image classes distribution is shown in fig 2.

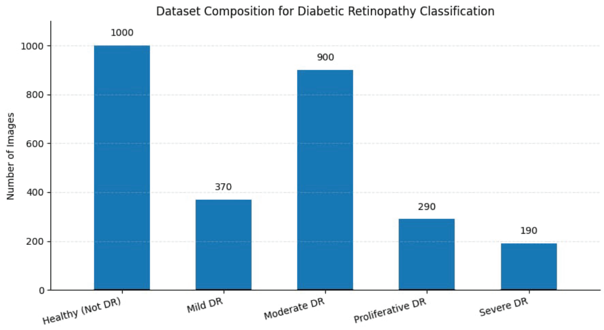


Fig. 2: Classification Of Dataset

B. Data Preprocessing

The raw fundus images go through the following preprocessing steps to improve quality and get the data ready for processing.

- **Resizing and Intensity Normalization**: Resizing, ensuring that all images maintain the same dimensions and pixel intensity ranges.
- **Noise Reduction**: removes any background noise and improves clarity by applying filters.
- **Contrast Enhancement**: improves visibility of important features by enhancing intensity differences between regions.
- **Data Augmentation**: Techniques like scaling, rotation, and flipping are applied to images to increase dataset similarity and reduce over-sizing.

C. CNN-Based Diabetic Retinopathy Classification

The convolutional Neural Network (CNN) is applied for automatic feature extraction and classification. The architecture contains:

1) **Input Layer**: Accepts retinal fundus images and passes the raw pixel intensity data into the network for feature extraction.
2) **Convolutional Layer**: Extracts high-level features such as blood vessels, exudates, and microaneurysms by applying learnable filters to capture spatial patterns.
3) **Activation Layer (ReLU)**: Introduces non-linearity into the model by replacing all negative pixel values in the feature map with zero, allowing the network to learn complex patterns.
4) **Pooling Layer**: Reduces the spatial dimensions of the feature maps through down-sampling (e.g., Max Pooling), which decreases computational load and controls overfitting.
5) **Flattening**: Transforms the multi-dimensional feature maps into a 1D feature vector to prepare the data for the dense layers.
6) **Fully Connected (Dense) Layer**: Integrates the global features extracted by the previous layers to map the learned representations to the target classes.
7) **Softmax/Output Layer**: Applies an activation function to generate a probability distribution across the output classes:
   - **Binary Classification**: DR vs. No DR.
   - **Multi-class Classification**:Mild,moderate,severe,No DR.

D. Model Traning and optimization

The model is trained using a feed-forward neural network implemented in PyTorch. Text input patterns are first transformed into numerical features using a Bag-of-Words representation. During training, the network minimizes classification error using the Cross-Entropy loss function and is optimized with the Adam optimizer. Training is carried out for a fixed number of epochs with a predefined batch size and learning rate. After training is completed, the learned model weights, along with the vocabulary and class labels, are saved for future prediction and deployment.

E. Evaluation Metrics

The trained model is evaluated using a common evaluation measure to check how well it classifies:

1) **Accuracy**: Measures the proportion of total predictions that are correct.
2) **Precision**: Represents the ratio of correctly predicted positive observations to the total predicted positives.
3) **Recall**: Measures the ratio of correctly predicted positive observations to all observations in the actual class.
4) **F1-Score**: The harmonic mean of Precision and Recall, providing a balance between the two.

5) **ROC-AUC**: Represents the model's ability to discriminate between classes across all possible classification thresholds.

III. SYSTEM ARCHITECTURE AND MATHEMATICAL APPROACH

A. *System Architecture*

The proposed system architecture represents an integrated framework for automated diabetic retinopathy detection and severity classification using retinal fundus images. The system is designed to support both patients and doctors through secure login and registration mechanisms, ensuring role-based access control. All authentication details, uploaded images, and diagnostic results are securely maintained in a SQLite database, which acts as the central repository of the system. This database enables reliable data storage and seamless communication between user interfaces and backend processing modules while preserving data integrity and confidentiality.

Once authenticated, patients are allowed to upload retinal fundus images through the patient interface, while doctors can access and review these images via authorized credentials. The uploaded fundus images are stored in the database and forwarded to the image analysis pipeline as system input. Before analysis, the images undergo a pre-processing stage that includes normalization, resizing, and data augmentation. These operations improve image quality, standardize image dimensions, and increase dataset variability, thereby enhancing the robustness and generalization capability of the deep learning model.

After pre-processing, the refined fundus images are passed to the feature extraction module based on Convolutional Neural Network layers. The CNN automatically learns discriminative retinal features such as microaneurysms, hemorrhages, exudates, and blood vessel patterns that are indicative of diabetic retinopathy. These learned features are subsequently used by the severity classification module to determine the stage of the disease. The classification process enables accurate differentiation between various severity levels, supporting early diagnosis and timely medical intervention.

Finally, the predicted results are presented through a unified patient and doctor dashboard that offers clear visualization of diagnostic outcomes. The system generates a comprehensive report containing the severity classification and relevant diagnostic insights. Additionally, the chatbot is integrated to assist users with basic queries related to the diagnosis and system usage. Overall, the proposed architecture ensures a secure, scalable, and clinically effective solution by integrating authentication, database management, deep learning-based analysis, and user-centric reporting into a single platform.

B. *Mathematical Approach*

1) *System Representation*: The proposed system is mathematically represented as:

$$S = I, P, O \tag{1}$$

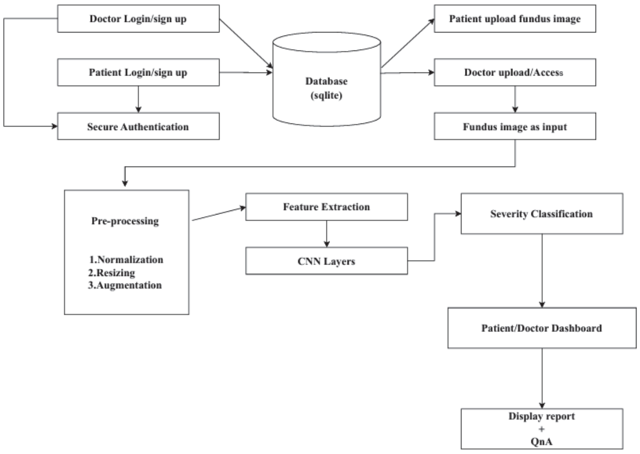


Fig. 3: System Architecture of the Diabetic Retinopathy Detection System.

Where: I → Input P → Processing (CNN model) O → Output

- **Input (I)**

$$I = I1, I2, \ldots, In \tag{2}$$

Where I represents a retinal fundus image. Each image is resized and normalized before processing.

2) *Processing (P)*: Processing is performed using a Convolutional Neural Network and can be represented as a function:

$$P = f(I) \tag{3}$$

- **Convolution Layer**

$$Fij^{(k)} = \sum_{m} \sum_{n} I(i+m, j+n).W^{k}_{mn} + b(k) \tag{4}$$

Where: W^k is the convolution kernel.
b^k is the bias term.
F^k is the feature map.

- **ReLU Activation**

$$A^{(k)}_{ij} = \max(0, F^{(k)}_{ij}) \tag{5}$$

Introduces non-linearity and removes negative values.

- **Pooling Layer**

$$P^{(k)}_{ij} = \max_{(m,n)\in R} A^{(k)}_{i+m,j+n} \tag{6}$$

Reduces spatial dimensions while retaining important features.

- **Flattening Layer**

$$V = Flatten(P) \tag{7}$$

Converts feature maps into a 1-D feature vector.

- **Flattening Layer**

$$V = Flatten(P) \tag{8}$$

Converts feature maps into a 1-D feature vector.

- **Fully Connected Layer**

$$Z = W_f V + b_f \tag{9}$$

Combines learned features for classification.

- **Softmax Classification**

$$y_i = \frac{e^{Z_i}}{\sum_{j=1}^{C} e^{Z_j}} \tag{10}$$

C is the number of classes and y_i is probability of class i.

4) *Loss Function*: The model minimizes categorical cross-entropy loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=0}^{3} y_{i,j} log(\hat{y}_{i,j}) \tag{11}$$

5) *Evaluation Metrics*: The performance of the model is evaluated using standard metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{13}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{14}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{15}$$

Here,TP, TN, FP, and FN denote the number of true positives, true negatives, false positives, and false negatives, respectively.

IV. RESULTS AND PERFORMANCE ANALYSIS

A. Dataset Overview

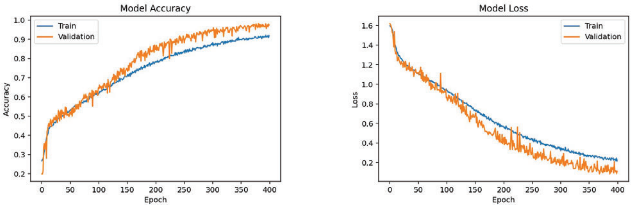
After preprocessing, normalization, and augmentation, the Diabetic Retinopathy Dataset from Kaggle was divided into training, validation, and testing subsets to support multi-class classification of diabetic retinopathy severity. The dataset included five categories representing severity levels: Healthy, Mild DR, Moderate DR, Severe DR, Proliferative DR.

Dataset Split	Healthy	Mild	Moderate	Severe	Prolif.	Total
Training	800	296	720	152	232	2200
Validation	200	74	180	38	58	275
Testing	200	74	180	38	58	550

TABLE I: Dataset Split for Multi-Class Diabetic Retinopathy Classification

B. Training and Validation Performance

Fig. 4 illustrates the training and validation accuracy and loss curves of the proposed CNN model. The curves indicate stable learning behavior with consistent improvement across epochs.

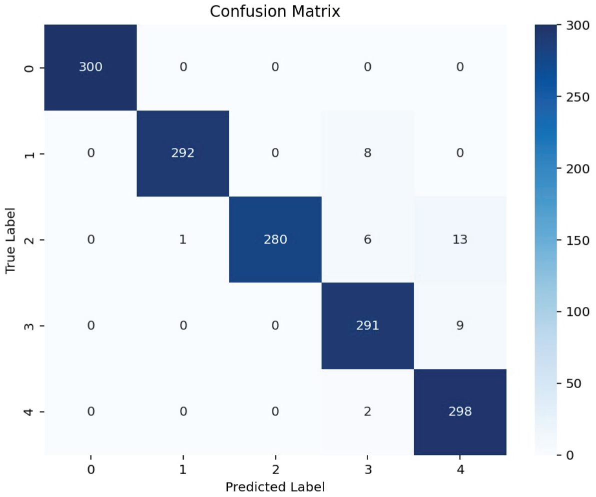


(a) Accuracy (b) Loss

Fig. 4: Training and validation accuracy and loss curves of the proposed CNN model.

C. Confusion Matrix Analysis

The confusion matrix in Fig. X illustrates the model's classification behaviour across the five diabetic retinopathy classes. Based on the actual class labels, the confusion matrix shows both accurate and inaccurate predictions.



True Label \ Predicted Label	0	1	2	3	4
0	300	0	0	0	0
1	0	292	0	8	0
2	0	1	280	6	13
3	0	0	0	291	9
4	0	0	0	2	298

Fig. 5: Confusion matrix of the proposed CNN model on the test dataset.

Observations:

1) The dominant diagonal values show that the model performs well in all classes, correctly classifying most of the Healthy, Mild, Moderate, Severe, and Proliferative DR samples.
2) Due to subtle visual differences and overlapping retinal lesion patterns, there is a limited degree of misclassification between adjacent severity levels, especially between Moderate, Severe, and Proliferative DR classes.
3) The model's strong ability to correctly differentiate between normal and pathological retinal images is demonstrated by the Healthy (No DR) class's highest recall.

D. *Performance Metrics*

Table II presents class-wise evaluation metrics derived from the test dataset. The model achieved a macro average F1-score of 97.41% indicating balanced classification performance.

Class	Precision (%)	Recall (%)	F1-Score (%)	Support
No DR	100.00	100.00	100.00	300
Mild	99.66	97.33	98.48	300
Moderate	100.00	93.33	96.55	300
Severe	94.79	97.00	95.88	300
Proliferative	93.13	99.33	96.13	300

TABLE II: Class-wise Performance Metrics

E. *Comparison with Existing Models*

The proposed model's performance was compared with existing CNN-based architectures from previous literature. Table III highlights that the proposed CNN achieves superior classification accuracy compared to conventional architectures such as VGG16, ResNet50, and the base CNN reported in the reference paper basepaper.

Model	Accuracy (%)	Source
AlexNet	92.80	Springer (2023)
VGG16	94.50	Springer (2023)
ResNet50	95.47	Springer (2023)
Hybrid	94.00	IEEE Access (2024)
Vision Transformer (ViT)	95.00	Vision Transformer DR Study (2023)
Proposed CNN Model	**96.23**	**Proposed Work**

TABLE III: Performance Comparison with Existing Models

F. *Summary of Results*

Table IV presents the final summary of experimental outcomes. The model demonstrated consistent performance across training and testing phases, achieving high generalization capability.

Metric	Achieved Value (%)
Training Accuracy	96.31
Test Accuracy	97.41
Precision (Macro Avg.)	97.51
Recall (Macro Avg.)	97.40
F1-Score (Macro Avg.)	97.41

TABLE IV: Summary of Overall CNN Performance

These results confirm that the proposed custom CNN effectively distinguishes between NO DR,Mild DR,Moderate DR,Severe DR and proliferative DR and generalizes well across unseen samples.

V. CONCLUSION AND FUTURE WORK

The suggested system effectively uses CNN-based deep learning techniques to demonstrate an automated diabetic retinopathy detection framework. The system correctly predicts DR stages like No DR, Mild DR, Moderate DR, and Severe DR by processing fundus images through image cleaning and feature learning. The results are displayed via a web dashboard.This method minimises human error, lowers manual labour, and provides clinicians with accurate, real-time predictions, all of which promote early diagnosis and better patient outcomes.To improve robustness and lesion bias.

Future work might train the model on bigger, multi-institutional datasets. By emphasising pathological areas, explainable AI methods like Grad-CAM can enhance clinical interpretability. To improve practical healthcare, the system can be expanded to include lightweight model deployment for real-time use, multi-disease retinal screening, and integration with clinical decision support systems.

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